Amendments to the Claims

Please amend Claims 1, 10, 11, and 21 through 25. Please add new Claims 26 through 64. This Claim Listing below will replace all prior versions of the claims in the application:

Claim Listing:

1. (Currently amended) A computer-implemented method for modeling a non-linear empirical process, said method comprising the steps of:

   creating an initial model generally corresponding to the non-linear empirical process to be modeled, the initial model having a base non-linear function, an initial input and an initial output;

   constructing a non-linear network model based on the initial model, the non-linear network model having (a) multiple inputs based on the initial input and (b) a global behavior for the non-linear network model as a whole that conforms generally to the initial output, the global behavior being at least in regions of sparse initial input; and

   calibrating the non-linear network model based on empirical inputs of the non-linear empirical process by using a bound on an analytical derivative of the base non-linear function that allows global properties including at least a global minimum value and a global maximum value of the analytical derivatives to be calculated directly from model coefficients, the global properties used to produce, via a constrained nonlinear optimization method, an analytically constrained model with global behavior, the constrained model ~~providing~~ enabling precision control of the non-linear empirical process.

2. (Original) The method of Claim 1, wherein the step of creating the initial model includes specifying a general shape of a gain trajectory for the non-linear empirical process.

3. (Original) The method of Claim 1, wherein the step of creating the initial model includes specifying a non-linear transfer function suitable for use in approximating the non-linear empirical process.

4. (Original) The method of Claim 3, wherein the non-linear network includes interconnected transformation elements and the step of constructing the non-linear network includes incorporating the non-linear transfer function into at least one transformation element.

5. (Previously presented) The method of Claim 4, wherein the step of calibrating the non-linear model includes setting constraints by taking a bounded derivative of the non-linear transfer function.

6. (Original) The method of Claim 5, wherein the non-linear transfer function includes the log of a hyperbolic cosine function.

7. (Previously presented) The method of Claim 1, wherein the non-linear network model is based on a layered network architecture having a feedforward network of nodes with input/output relationships to each other, the feedforward network having transformation elements; each transformation element having a non-linear transfer function, a weighted input coefficient and a weighted output coefficient; and the step of calibrating the non-linear network model includes constraining the global behavior of the non-linear network model to a monotonic transformation based on the initial input by pairing the weighted input and output coefficients for each transformation element in a complementary manner to provide the monotonic transformation.

8. (Previously presented) The method of Claim 1, wherein the step of calibrating the non-linear network model comprises adjusting the calibration based on information provided by an advisory model that represents another model of the non-linear empirical process that is different from the initial model, the non-linear network model, and the constrained model.

9. (Original) The method of Claim 8, wherein the advisory model is a first principles model of the non-linear empirical process.

10. (Currently amended) ~~The method of Claim 1,~~ A computer-implemented method for modeling a non-linear empirical process, and controlling a greater process, said method comprising the steps of:

creating an initial model generally corresponding to the non-linear empirical process to be modeled, the initial model having a base non-linear function, an initial input and an initial output;

constructing a non-linear network model based on the initial model, the non-linear network model having (a) multiple inputs based on the initial input and (b) a global behavior for the non-linear network model as a whole that conforms generally to the initial output, the global behavior being at least in regions of sparse initial input; and

calibrating the non-linear network model based on empirical inputs of the non-linear empirical process by using a bound on an analytical derivative of the base non-linear function that allows global properties including at least a global minimum value and a global maximum value of the analytical derivatives to be calculated directly from model coefficients, the global properties used to produce, via a constrained nonlinear optimization method, an analytically constrained model with global behavior, the constrained model enabling precision control of the non-linear empirical process, ~~wherein~~ the non-linear empirical process [[is]] being part of [[a]] the greater process, and ~~the method further includes the step of~~ deploying the constrained model in a controller that controls the greater process.

11. (Currently amended) A computer apparatus for building a model for modeling a non-linear empirical process, comprising:

a model creator for creating an initial model generally corresponding to the non-linear empirical process to be modeled, the initial model having a base non-linear function, an initial input and an initial output, the global behavior being at least in regions of sparse initial input;

a model constructor coupled to the model creator for constructing a non-linear network model based on the initial model, the non-linear network model having multiple inputs based on the initial input and a global behavior for the non-linear network model as a whole that conforms generally to the initial output; and

a calibrator coupled to the model constructor for calibrating the non-linear network model based on empirical inputs of the non-linear empirical process by using a bound on an analytical derivative of the base non-linear function that allows global properties including at least a global minimum value and a global maximum value of the analytical derivatives to be calculated directly from model coefficients, the global properties used to produce, via a constrained nonlinear optimization method, an analytically constrained model with global behavior, the constrained model ~~providing~~ enabling precision control of the non-linear empirical process.

12. (Original) The computer apparatus of Claim 11, wherein the model creator specifies a general shape of a gain trajectory for the non-linear empirical process.

13. (Original) The computer apparatus of Claim 11, wherein the model creator specifies a non-linear transfer function suitable for use in approximating the non-linear empirical process.

14. (Original) The computer apparatus of Claim 13, wherein the non-linear network includes interconnected transformation elements and the model constructor incorporates the non-linear transfer function into at least one transformation element.

15. (Previously presented) The computer apparatus of Claim 14, wherein the calibrator sets constraints by taking a bounded derivative of the non-linear transfer function.

16. (Original) The computer apparatus of Claim 15, wherein the non-linear transfer function includes the log of a hyperbolic cosine function.

17. (Previously presented) The computer apparatus of Claim 11, wherein the model constructor constructs the non-linear network model based on a layered network architecture having a feedforward network of nodes with input/output relationships to each other, the feedforward network having transformation elements, each transformation element having a non-linear transfer function, a weighted input coefficient and a weighted output coefficient; and

the calibrator constrains the global behavior of the non-linear network model to a monotonic transformation based on the initial input by pairing the weighted input and output coefficients for each transformation element in a complementary manner to provide the monotonic transformation.

18. (Previously presented) The computer apparatus of Claim 11, further comprising an advisory model that represents another model of the non-linear empirical process that is different from the initial model, the non-linear network model, and the constrained model; and

wherein the calibrator adjusts the calibration based on information provided by the advisory model.

19. (Original) The computer apparatus of Claim 18, wherein the advisory model is a first principles model of the non-linear empirical process.

20. (Previously presented) The computer apparatus of Claim 11, wherein the non-linear empirical process is part of a greater process managed by a controller coupled to controller optimizer, and the controller optimizer communicates the constrained model to the controller for deployment in the controller.

21. (Currently amended) A computer program product that includes a computer usable medium having computer program instructions stored thereon for building a model for modeling a non-linear empirical process, such that the computer program instructions, when performed by a digital processor, cause the digital processor to:

create an initial model generally corresponding to the non-linear empirical process to be modeled, the initial model having a base non-linear function, an initial input and an initial output;

construct a non-linear network model based on the initial model, the non-linear network model having multiple inputs based on the initial input and a global behavior for the non-linear network model as a whole that conforms generally to the initial output, the global behavior being at least in regions of sparse initial input; and

calibrate the non-linear network model based on empirical inputs of the non-linear empirical process by using a bound on an analytical derivative of the base non-linear function that allows global properties including at least a global minimum value and a global maximum value of the analytical derivatives to be calculated directly from model coefficients, the global properties used to produce, via a constrained nonlinear optimization method, an analytically constrained model with global behavior, the constrained model ~~providing~~ enabling precision control of the non-linear empirical process.

22. (Currently amended) A computer-implemented method for building a model for modeling a polymer process, said method comprising the steps of:

specifying a base non-linear function for an initial model generally corresponding to the polymer process to be modeled, the initial model including an initial input and an initial output and the base non-linear function including a log of a hyperbolic cosine function;

constructing a non-linear network model based on the initial model and including the base non-linear function, the non-linear network model having multiple inputs based on the initial input and a global behavior for the non-linear network model as a whole that conforms generally to the initial output; and

calibrating the non-linear network model based on empirical inputs of the non-linear empirical process by using a bound on a derivative of the base non-linear function to constrain parameters of the model in order to produce a constrained model with global behavior, the constrained model providing optimized approximations to a process controller for controlling the polymer process.

23. (Currently amended) A computer apparatus for building a model for modeling a polymer process; comprising:

a model creator for specifying a base non-linear function for an initial model generally corresponding to the polymer process to be modeled, the initial model including an initial input and an initial output and the base non-linear function including a log of a hyperbolic cosine function;

a model constructor coupled to the model creator for constructing a non-linear network model based on the initial model and including the base non-linear function, the non-linear network model having multiple inputs based on the initial input and a global behavior for the non-linear network model as a whole that conforms generally to the initial output; and

a calibrator coupled to the model constructor for calibrating the non-linear network model based on empirical inputs of the non-linear empirical process by using a bound on a derivative of the base non-linear function to constrain parameters of the model in order to produce a constrained model with global behavior, the constrained model providing optimized approximations to a process controller for controlling the polymer process.

24. (Currently amended) A computer program product that includes a computer usable medium having computer program instructions stored thereon for building a model for modeling a polymer process, such that the computer program instructions, when performed by a digital processor, cause the digital processor to:

specify a base non-linear function for an initial model generally corresponding to the polymer process to be modeled, the initial model including an initial input and an initial output and the base non-linear function including a log of a hyperbolic cosine function;

construct a non-linear network model based on the initial model and including the base non-linear function, the non-linear network model having multiple inputs based on the initial input and a global behavior for the non-linear network model as a whole that conforms generally to the initial output; and

calibrate the non-linear network model based on empirical inputs of the non-linear empirical process by using a bounded derivative of the base non-linear function to constrain the parameters of the model in order to produce a constrained model with global behavior, the constrained model providing optimized approximations to a process controller for controlling the polymer process.

25. (Currently amended) A computer-implemented method for modeling a non-linear empirical process, the method comprising the steps of:

creating an initial model generally corresponding to the non-linear empirical process to be modeled, the initial model having a base non-linear function, an initial input and an initial output;

constructing a non-linear network model based on the initial model, the non-linear network model having (a) multiple inputs based on the initial input and (b) a global behavior for the non-linear network model as a whole that conforms generally to the initial output, the global behavior being at least in regions of sparse initial input or in regions of missing initial input; and

calibrating the non-linear network model based on empirical inputs of the non-linear empirical process by using a bound on a derivative of the base non-linear function to constrain parameters of the model to produce a constrained model with global behavior of the non-linear network model, the constrained model ~~providing~~ enabling precision control of the non-linear empirical process.

26. (New) A computer implemented method for modeling a non-linear empirical process, said method comprising the steps of:

creating an initial model generally corresponding to the non-linear empirical process to be modeled, the initial model having a base non linear function, an initial input and an initial output;

constructing a non-linear network model based on the initial model, the non-linear network model having (a) multiple inputs based on the initial input and (b) a global behavior for the non-linear network model as a whole that conforms generally to the initial output, the global behavior being at least in regions of sparse initial input; and

calibrating the non-linear network model based on empirical inputs of the non-linear empirical process by using a bound on an analytical derivative of the base non-linear function that allows global properties including at least a global minimum value and a global maximum value of the analytical derivatives to be calculated and manipulated directly from model coefficients, the global properties used to produce, via a

constrained nonlinear optimization method, an analytically constrained model with global behavior, the constrained model enabling precision control of the non linear empirical process.

27. (New) A computer implemented method for modeling a non-linear empirical process, said method comprising the steps of:

creating an initial model generally corresponding to the non-linear empirical process to be modeled, the initial model having a base non linear function, an initial input and an initial output;

constructing a non-linear network model based on the initial model, the non-linear network model having (a) multiple inputs based on the initial input and (b) a global behavior for the non-linear network model as a whole that conforms generally to the initial output, the global behavior being at least in regions of sparse initial input; and

calibrating the non-linear network model based on empirical inputs of the non-linear empirical process by using a bound on an analytical derivative of the base non-linear function that allows global properties including at least a global minimum value and a global maximum value of the analytical derivatives to be calculated and manipulated directly from model coefficients, the global properties used to produce, via a constrained nonlinear optimization method, an analytically constrained model with global behavior, the constrained model enabling precision control of the non linear empirical process, and the model coefficients being manipulated by using a modified base non-linear function.

28. (New) A computer implemented method for modeling a non-linear empirical process, said method comprising the steps of:

creating an initial model generally corresponding to the non-linear empirical process to be modeled, the initial model having a base non linear function, an initial input and an initial output;

constructing a non-linear network model based on the initial model, the non-linear network model having (a) multiple inputs based on the initial input and (b) a global

behavior for the non-linear network model as a whole that conforms generally to the initial output, the global behavior being at least in regions of sparse initial input; and

calibrating the non-linear network model based on empirical inputs of the non-linear empirical process by using a bound on an analytical derivative of the base non-linear function that allows global properties including at least a global minimum value and a global maximum value of the analytical derivatives to be calculated and manipulated directly from model coefficients, the global properties used to produce, via a constrained nonlinear optimization method, an analytically constrained model with global behavior, the constrained model enabling precision control of the non-linear empirical process, and the model coefficients being manipulated by using a modified base non-linear function that excludes at least one of a hyperbolic tangent function, a radial basis function, and a sigmoid function, the base non-linear function has a global minimum or a global maximum first derivative that is independent of the model coefficients.

29. (New) A computer implemented method for modeling a non-linear empirical process, said method comprising the steps of:

creating an initial model generally corresponding to the non-linear empirical process to be modeled, the initial model having a base non linear function, an initial input and an initial output;

constructing a non-linear network model based on the initial model, the non-linear network model having (a) multiple inputs based on the initial input and (b) a global behavior for the non-linear network model as a whole that conforms generally to the initial output, the global behavior being at least in regions of sparse initial input; and

calibrating the non-linear network model based on empirical inputs of the non-linear empirical process by using a bound on an analytical derivative of the base non linear function that allows global properties including at least a global minimum value and a global maximum value of the analytical derivatives to be calculated and manipulated directly from model coefficients, the global properties used to produce, via a constrained nonlinear optimization method, an analytically constrained model with

global behavior, the constrained model enabling precision control of the non linear empirical process, the global maximum and minimum values of the analytical derivatives both being a free function of the model coefficients.

30. (New) The computer implemented method of Claim 29, wherein the base nonlinear function excludes at least one of a hyperbolic tangent function, a radial basis function, a sigmoid function, and wherein a global minimum or a global maximum first derivative is independent of the model coefficients.

31. (New) A computer accessible memory medium that stores program instructions for model predictive control and optimization of a nonlinear process, wherein the program instructions are executable by a processor to implement:

a parametric universal nonlinear dynamic approximator for predictive optimization or control of a nonlinear process, comprising:

a parameterized dynamic model, operable to model the nonlinear process, wherein the parameterized dynamic model comprises one or more parameters that are not inputs or outputs of the nonlinear process; and

a nonlinear approximator, operable to model dependencies of the one or more parameters of the parameterized dynamic model upon operating conditions of the nonlinear process;

wherein the parametric universal nonlinear dynamic approximator is operable to predict process outputs necessary for predictive control and optimization of the nonlinear process by:

operating the nonlinear approximator to:

receive one or more process operating conditions, including one or more process inputs; and

generate values for the one or more parameters of the parameterized dynamic model based on the process operating conditions; and

operating the parameterized dynamic model to:

receive the values of the one or more parameters;

receive the one or more process inputs;

generate one or more predicted process outputs based on the received one or more parameters and the received one or more process inputs; and

store the one or more predicted process outputs

32. (New) The memory medium of claim 31, wherein the one or more predicted process outputs are dependent on the one or more process inputs, the values of the one or more parameters, and past values of the process inputs and outputs.

33. (New) The memory medium of claim 32,

wherein the nonlinear approximator and the parameterized dynamic model of the parametric universal nonlinear dynamic approximator are operable to be trained in an integrated manner by an optimization process.

34. (New) The memory medium of claim 33,

wherein the parametric universal nonlinear dynamic approximator is operable to be coupled to the nonlinear process or a representation of the nonlinear process;

wherein the nonlinear process is operable to receive the one or more process inputs and produce the one or more process outputs;

wherein the optimization process is operable to determine model errors based on the one or more process outputs and the one or more predicted process outputs; and

wherein the optimization process is operable to adaptively train the parametric universal nonlinear dynamic approximator in an iterative manner using the model errors and an optimizer.

35. (New) The memory medium of claim 34, wherein, in training the parametric universal nonlinear dynamic approximator in an iterative manner using the model errors and an optimizer, the optimization process is operable to:

identify process inputs and outputs (I/O);

determine an order of the parameterized dynamic model, wherein the order specifies the number of parameters comprised in the parameterized dynamic

model;

collect data representing process operating conditions;

determine constraints on behavior of the parametric universal nonlinear dynamic approximator from prior knowledge, including one or more constraints for the nonlinear approximator for modeling dependencies of the one or more parameters of the parameterized dynamic model;

formulate an optimization problem;

execute an optimization algorithm to determine the dependencies of the parameters of the parameterized dynamic model upon operating conditions of the nonlinear process subject to the determined constraints by solving the optimization problem, thereby training the nonlinear approximator; and

verify compliance of the parametric universal nonlinear dynamic approximator with the specified constraints.

36. (New) The memory medium of claim 35, wherein, in verifying the compliance of the parametric universal nonlinear dynamic approximator with the specified constraints, the optimization process is operable to:

use interval arithmetic over the global input region; and/or

use interval arithmetic with input-region partitioning.

37. (New) The memory medium of claim 35, wherein in determining the order of the parameterized dynamic model, the optimization process is operable to:

execute the optimization algorithm to determine an optimal order of the parameterized dynamic model.

38. (New) The memory medium of claim 35, wherein the optimization process is operable to determine the order of the parameterized dynamic model and train the nonlinear approximator concurrently.

39. (New) The memory medium of claim 35, wherein in formulating the optimization problem, the optimization process is operable to determine or modify an objective function.

40. (New) The memory medium of claim 35, wherein, in solving the optimization problem, the optimization process is operable to solve an objective function subject to the determined constraints.

41. (New) The memory medium of claim 32, wherein, after being trained, the overall behavior of the parametric universal nonlinear dynamic approximator is consistent with prior knowledge of the nonlinear process.

42. (New) The memory medium of claim 31, wherein the nonlinear approximator comprises one or more of:
a neural network;
a support vector machine;
a statistical model;
a parametric description of the nonlinear process;
a Fourier series model; or
an empirical model.

43. (New) The memory medium of claim 31, wherein the nonlinear approximator comprises a universal nonlinear approximator.

44. (New) The memory medium of claim 31, wherein the nonlinear approximator includes a feedback loop, and wherein the feedback loop is operable to provide output of the nonlinear approximator from a previous cycle as input to the nonlinear approximator for a current cycle.

45. (New) The memory medium of claim 31, wherein the parameterized dynamic model comprises a multi-input, multi-output (MIMO) dynamic model implemented with a set of difference equations.

46. (New) The memory medium of claim 45, wherein the set of difference equations comprises a set of discrete time polynomials.

47. (New) The memory medium of claim 45, wherein the one or more process inputs are received from one or more of:

the nonlinear process; or

a representation of the nonlinear process.

48. (New) The memory medium of claim 47, wherein the representation of the nonlinear process comprises one or more of:

a first principles model;

a statistical model;

a parametric description of the nonlinear process;

a Fourier series model;

an empirical model; or

empirical data.

49. (New) The memory of medium claim 31, wherein the parametric universal nonlinear dynamic approximator is operable to be coupled to the nonlinear process, wherein the parametric universal nonlinear dynamic approximator is further operable to be coupled to a control process, wherein the control process is operable to:

a) initialize a parametric universal nonlinear dynamic approximator to a current status of the nonlinear process, comprising process inputs and outputs, by:

initializing inputs to a nonlinear approximator comprised in the parametric universal nonlinear dynamic approximator, wherein the nonlinear approximator is trained to model dependencies of one or more parameters of a parameterized dynamic model of the nonlinear process comprised in the parametric universal nonlinear dynamic approximator upon operating condition of the nonlinear process;

executing the trained nonlinear approximator to determine initial values for the one or more parameters of the parameterized dynamic model based on the current status of the nonlinear process; and

initializing the parameterized dynamic model with the determined values for the one or more parameters;

b) formulate an optimization problem, including specifying an objective for the nonlinear process;

c) generate a profile of manipulated variables for the nonlinear process over a control horizon in accordance with the specified objective for the nonlinear process;

d) operate the parametric universal nonlinear dynamic approximator in accordance with the generated profile of manipulated variables, thereby generating predicted outputs for the nonlinear process;

e) determine a deviation of the predicted outputs from a desired behavior of the nonlinear process;

f) repeat b) – e) one or more times to determine an optimal profile of manipulated variables in accordance with the specified objective for the nonlinear process;

g) operate the nonlinear process in accordance with the optimal profile of manipulated variables, thereby generating process output; and

repeat a) – g) one ore more times to dynamically control the nonlinear process.

50. (New) A method for training a parametric universal nonlinear dynamic approximator of a nonlinear process, the method comprising:

identifying process inputs and outputs (I/O);

determining an order for a parameterized dynamic model comprised in the parametric universal nonlinear dynamic approximator, wherein the order specifies the number of parameters for the parameterized dynamic model, and wherein the parameters of the parameterized dynamic model are not inputs or outputs of the nonlinear process;

determining a structure for a nonlinear approximator comprised in the parametric universal nonlinear dynamic approximator for modeling dependencies of the parameters of the parameterized dynamic model upon operating conditions of the nonlinear process;

collecting data for the identified process I/O;

determining constraints on behavior of the parametric universal nonlinear

dynamic approximator from prior knowledge, including one or more constraints for the nonlinear approximator for modeling dependencies of the one or more parameters of the parameterized dynamic model;

formulating an optimization problem for training the nonlinear approximator;

executing an optimization algorithm to train the nonlinear approximator subject to the determined constraints by solving the optimization problem, thereby determining the dependencies of the parameters of the parameterized dynamic model upon operating conditions of the process, wherein outputs of the nonlinear approximator are not outputs of the nonlinear process;

verifying compliance of the parametric universal nonlinear dynamic approximator with the specified constraints;

storing the trained nonlinear approximator and the parameterized dynamic model, wherein the stored nonlinear approximator and the parameterized dynamic model compose a trained parametric universal nonlinear dynamic approximator; and

wherein the trained parametric universal nonlinear dynamic approximator is usable to optimize and control the nonlinear process.

51. (New) The method of claim 50, wherein said verifying the compliance of the parametric universal nonlinear dynamic approximator with the specified constraints comprises one or more of:

using interval arithmetic over the global input region; or

using interval arithmetic with input-region partitioning.

52. (New) The method of claim 50, wherein said determining the order comprises;

executing the optimization algorithm to determine an optimal order of the parameterized dynamic model.

53. (New) The method of claim 50, wherein said executing the optimization algorithm to determine the optimal order of the parameterized dynamic model and said executing the optimization algorithm to determine dependencies of the parameters of the parameterized dynamic model are performed concurrently.

54. (New) The method of claim 50, wherein formulating the optimization problem comprises:

determining an objective function; and

wherein solving the optimization problem comprises:

solving the objective function subject to the determined constraints.

55. (New) A system for training a parametric universal nonlinear dynamic approximator of a nonlinear process, the system comprising:

means for identifying process inputs and outputs (I/O);

means for determining an order for a parameterized dynamic model comprised in the parametric universal nonlinear dynamic approximator, wherein the order specifies the number of parameters for the parameterized dynamic model, and wherein the parameters of the parameterized dynamic model are not inputs or outputs of the nonlinear process;

means for determining a structure for a nonlinear approximator comprised in the parametric universal nonlinear dynamic approximator for modeling dependencies of the parameters of the parameterized dynamic model upon operating conditions of the nonlinear process;

means for collecting data for the identified process I/O;

means for determining constraints on behavior of the parametric universal nonlinear dynamic approximator from prior knowledge, including one or more constraints for the nonlinear approximator for modeling dependencies of the one or more parameters of the parameterized dynamic model;

means for formulating an optimization problem for training the nonlinear approximator;

means for executing an optimization algorithm to train the nonlinear approximator subject to the determined constraints by solving the optimization problem, thereby determining the dependencies of the parameters of the parameterized dynamic model upon operating conditions of the process, wherein outputs of the nonlinear approximator are not outputs of the nonlinear process;

means for verifying compliance of the parametric universal nonlinear dynamic approximator with the specified constraints; and

means for storing the trained nonlinear approximator and the parameterized dynamic model, wherein the stored nonlinear approximator and the parameterized dynamic model compose a trained parametric universal dynamic approximator;

wherein the parametric universal nonlinear dynamic approximator is usable to optimize and control the nonlinear process.

56. (New) A method for controlling a nonlinear process, the method comprising:

a) initializing a parametric universal nonlinear dynamic approximator to a current status of the nonlinear process, comprising process inputs and outputs, said initializing comprising:

initializing inputs to a nonlinear approximator comprised in the parametric universal nonlinear dynamic approximator, wherein the nonlinear approximator is trained to model dependencies of one or more parameters of a parameterized dynamic model of the nonlinear process comprised in the parametric universal nonlinear dynamic approximator upon operating conditions of the nonlinear process;

executing the trained nonlinear approximator to determine initial values for the one or more parameters of the parameterized dynamic model based on the current status of the nonlinear process; and

initializing the parameterized dynamic model with the determined values for the one or more parameters;

b) formulating an optimization problem, including specifying an objective for the nonlinear process;

c) generating a profile of manipulated variables for the nonlinear process over a control horizon in accordance with the specified objective for the nonlinear process;

d) operating the parametric universal nonlinear dynamic approximator in accordance with the generated profile of manipulated variables, thereby generating predicted outputs for the nonlinear process;

e) determining a deviation of the predicted outputs from a desired behavior of the nonlinear process;

f) repeating b) – e) one or more times to determine an optimal profile of

manipulated variables in accordance with the specified objective for the nonlinear process;

g) operating the nonlinear process in accordance with the optimal profile of manipulated variables, thereby generating process output; and

repeating a) – g) one or more times to dynamically control the nonlinear process.

57. (New) The method of claim 56, further comprising:

h) modifying the optimization problem based on the input to the model;

wherein said repeating a) – g) comprises repeating a) – h).

58. (New) The method of claim 57, wherein said modifying the optimization problem comprises modifying one or more of:

constraints;

an objective function;

model parameters;

optimization parameters; and:

optimization data.

59. (New) A system for controlling a nonlinear process, the system comprising:

means for a) initializing a parametric universal nonlinear dynamic approximator to a current status of the nonlinear process, comprising process inputs and outputs, comprising:

means for initializing inputs to a nonlinear approximator comprised in the parametric universal nonlinear dynamic approximator, wherein the nonlinear approximator is trained to model dependencies of one or more parameters of a parameterized dynamic model of the nonlinear process comprised in the parametric universal nonlinear dynamic approximator upon operating conditions of the nonlinear process;

means for executing the trained nonlinear approximator to determine initial values for the one or more parameters of the parameterized dynamic model based on the current

status of the nonlinear process;

means for initializing the parameterized dynamic model with the determined values for one or more parameters;

means for b) formulating an optimization problem, including specifying an objective for the nonlinear process;

means for c) generating a profile of manipulated variables for the nonlinear process over a control horizon in accordance with the specified objective for the nonlinear process;

means for d) operating the parametric universal nonlinear dynamic approximator in accordance with the generated profile of manipulated variables, thereby generating predicted outputs for the nonlinear process;

means for e) determining a deviation of the predicted outputs from a desired behavior of the nonlinear process;

means for e) determining a deviation of the predicted outputs from a desired behavior of the nonlinear process;

means for f) repeating b) – e) one or more times to determine an optimal profile of manipulated variables in accordance with the specified objective for the nonlinear process;

means for g) operating the nonlinear processing accordance with the optimal profile of manipulated variables, thereby generating process output; and

means for repeating a) – g) one or more times to dynamically control the nonlinear process.

60. (New) A computer accessible memory medium that stores program instructions for model predictive control and optimization of a nonlinear process, wherein the program instructions are executable by a processor to implement:

a state space model for predictive optimization or control of a nonlinear process, comprising:

a state space dynamic model, operable to model the nonlinear process, wherein the state space dynamic model comprises one or more coefficients that are not inputs or outputs of the nonlinear process; and

a nonlinear approximator, operable to model dependencies of the one or more coefficients of the state space dynamic model upon operating conditions of the nonlinear process;

wherein the state space model is operable to predict process outputs necessary for predictive control and optimization of the nonlinear process by:

operating the nonlinear approximator to:

receive one or more process operating conditions, including one or more process inputs; and

generate values for the one or more coefficients of the state space dynamic model based on the process operating conditions; and

operating the state space dynamic model to:

receive the values of the one or more coefficients

receive the one or more process inputs;

generate one or more predicted process outputs based on the received one or more coefficients and the received one or more process inputs; and

store the one or more predicted process outputs

61. (New) A method for training a state space model of a nonlinear process, the method comprising:

identifying process inputs and outputs (I/O);

determining an order for a state space dynamic model comprised in the state space model, wherein the order specifies the number of coefficients for the state space dynamic model, and wherein the coefficients of the state space dynamic model are not inputs or outputs of the nonlinear process;

determining a structure for a nonlinear approximator comprised in the state space model for modeling dependencies of the coefficients of the state space dynamic model upon operating conditions of the nonlinear process;

collecting data for the identified process I/O;

determining constraints on behavior of the state space model from prior knowledge, including one or more constraints for the nonlinear approximator for modeling dependencies of the one or more coefficients of the state space dynamic

model;

formulating an optimization problem for training the nonlinear approximator;

executing an optimization algorithm to train the nonlinear approximator subject to the determined constraints by solving the optimization problem, thereby determining the dependencies of the coefficients of the state space dynamic model upon operating conditions of the process, wherein outputs of the nonlinear approximator are not outputs of the nonlinear process;

verifying compliance of the state space model with the specified constraints; and

storing the trained nonlinear approximator and the state space dynamic model,

wherein the stored nonlinear approximator and the state space dynamic model compose a trained state space model;

wherein the trained state space model is usable to optimize and control the nonlinear process.

62. (New) A system for training a state space model of a nonlinear process, the system comprising:

means for identifying process inputs and outputs (I/O);

means for determining an order for a state space dynamic model comprised in the state space model, wherein the order specifies the number of coefficients for the state space dynamic model, and wherein the coefficients of the state space dynamic model are not inputs or outputs of the nonlinear process;

means for determining a structure for a nonlinear approximator comprised in the state space model for modeling dependencies of the coefficients of the state space dynamic model upon operating conditions of the nonlinear process;

means for collecting data for the identified process I/O;

means for determining constraints on behavior of the state space model from prior knowledge, including one or more constraints for the nonlinear approximator for modeling dependencies of the one or more coefficients of the state space dynamic model;

means for formulating an optimization problem for training the nonlinear approximator;

means for executing an optimization algorithm to train the nonlinear

approximator subject to the determined constraints by solving the optimization problem, thereby determining the dependencies of the coefficients of the state space dynamic model upon operating conditions of the process, wherein outputs of the nonlinear approximator are not outputs of the nonlinear process;

means for verifying compliance of the state space model with the specified constraints; and

means for storing the trained nonlinear approximator and the state space dynamic model, wherein the stored nonlinear approximator and the state space dynamic model compose a trained state space model; and

wherein the state space model is usable to optimize and control the nonlinear process.

63. (New) A method for controlling a nonlinear process, the method comprising:

a) initializing a state space model to a current status of the nonlinear process, comprising process inputs and outputs, said initializing comprising:

initializing inputs to a nonlinear approximator comprised in the state space model, wherein the nonlinear approximator is trained to model dependencies of one or more coefficients of a state space dynamic model of the nonlinear process comprised in the state space model upon operating conditions of the nonlinear process;

executing the trained nonlinear approximator to determine initial values for the one or more coefficients of the state space dynamic model based on the current status of the nonlinear process; and

initializing the state space dynamic model with the determined values for the one or more coefficients;

b) formulating an optimization problem, including specifying an objective for the nonlinear process;

c) generating a profile of manipulated variables for the nonlinear process over a control horizon in accordance with the specified objective for the nonlinear process;

d) operating the state space model in accordance with the generated profile of manipulated variables, thereby generating predicted outputs for the nonlinear process;

e) determining a deviation of the predicted outputs from a desired behavior of

the nonlinear process;

f) repeating b) – e) one or more times to determine an optimal profile of manipulated variables in accordance with the specified objective for the nonlinear process;

g) operating the nonlinear process in accordance with the optimal profile of manipulated variables, thereby generating process output; and

repeating a) – g) one or more times to dynamically control the nonlinear process.

64. (New) A system for controlling a nonlinear process, the system comprising:

means for a) initializing a state space model to a current status of the nonlinear process, comprising process inputs and outputs, comprising:

means for initializing inputs to a nonlinear approximator comprised in the state space model, wherein the nonlinear approximator is trained to model dependencies of one or more coefficients of a state space dynamic model of the nonlinear process comprised in the state space model upon operating conditions of the nonlinear process;

means for executing the trained nonlinear approximator to determine initial values for the one or more coefficients of the state space dynamic model based on the current status of the nonlinear process;

means for initializing the state space dynamic model with the determined values for one or more coefficients;

means for b) formulating an optimization problem, including specifying an objective for the nonlinear process;

means for c) generating a profile of manipulated variables for the nonlinear process over a control horizon in accordance with the specified objective for the nonlinear process;

means for d) operating the state space model in accordance with the generated profile of manipulated variables, thereby generating predicted outputs for the nonlinear process;

means for e) determining a deviation of the predicted outputs from a desired behavior of the nonlinear process;

means for f) repeating b) – e) one or more times to determine an optimal profile of manipulated variables in accordance with the specified objective for the nonlinear process;

means for g) operating the nonlinear processing accordance with the optimal profile of manipulated variables, thereby generating process output; and

means for repeating a) – g) one or more times to dynamically control the nonlinear process.